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THE FACILITATING EFFECTS OF UNCERTAINTY IN LONG-TERM MANUAL CONTROL*

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SUMMARY

A 40-minute tracking task with different disturbance inputs has been used to look for the effects of reduced task demands on long-term manual control. The expected facilitating effects of task difficulty are hard to find. The decrements in performance over the run are no greater for the easier tasks. The detrimental effects of lower demand appear to be increased relative variability in performance, and possibly reduced performance on transition to unexpected, more difficult tasks.

An information measure, including the effects of "self-induced" uncertainty is developed as a work-load measure. There is a positive correlation between this "self-induced work-load" and performance decrement for the easiest task - just the opposite of what the facilitation hypothesis would predict.

THE FACILITATION HYPOTHESIS

Most people would agree that with increased automation there is a danger that the tasks left to the human operator might not be demanding enough; that somehow, a certain amount of task difficulty is required to facilitate human performance. These effects are expected to show up, if not over the short run, at least in long-term, low-complexity tasks.

The notion that a certain amount of stress is good is known variously as the "activation-" or "facilitation-hypothesis" or the Yerkes-Dodson Law.[1] It is usually represented as an inverted-U relationship between performance and "arousal". For this paper we use tracking error as the performance measure so the facilitation hypothesis would be represented as in Figure 1. (Note that there is expected to be an optimum stress between "boring" and "fatiguing".)

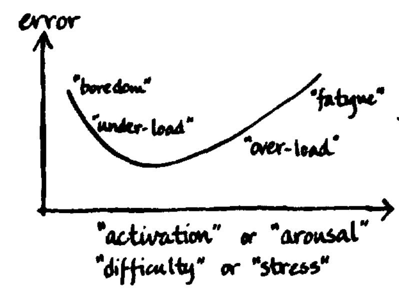

Figure 1. The facilitation hypothesis.

Monitoring and signal-detection tasks of low demand have been studied extensively within the vigilance paradigm.[2,3] Even though decrements in tracking performance follow the same trend as do decrements in detection performance, models of vigilance have not been applied to tracking and no measures of task difficulty have been developed which predict the effects of "under-load". Surprisingly, the literature contains little empirical support for the facilitation hypothesis.[4]

AN EXPERIMENT

To explore the effects of task difficulty on long-term manual control, subjects tracked for 40 minutes with one of four levels of difficulty. The dynamics were a double integrator ($1/s^2$); the control was a spring-centered stick. The display was a computer-generated image on a CRT that presented position and rate (heading) with a "perspective roadway".

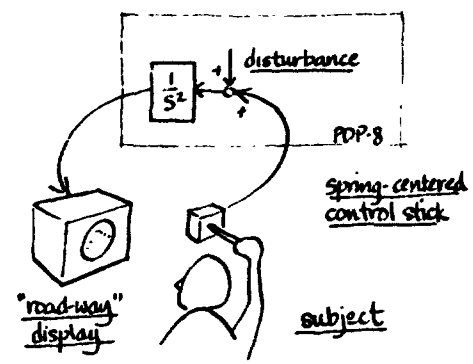

Figure 2. Schematic of experiment

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Four conditions of disturbance ("t... : difficulty") were used (A,B,C,D), including no-input (A). Each disturbance consisted of the sum of 9 sine waves added to the human operator's (h.o.) output. The task simulated driving down a straight road with random lateral wind gusts.

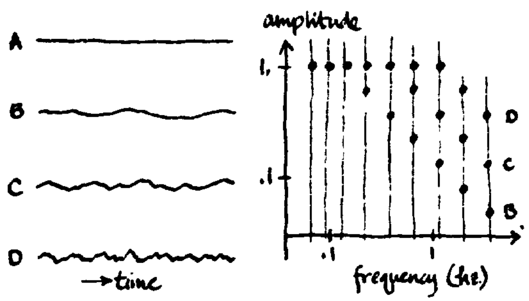
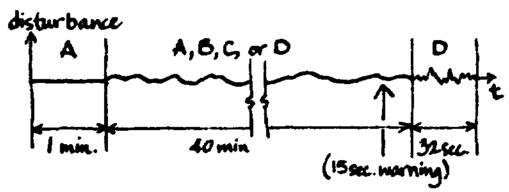


Figure 3. Disturbance samples and spectra.

The same disturbance was given for 40 minutes at which time the most difficulty disturbance (D) was given for the final 32 seconds. Each of the four conditions was given twice: once with and once without a warning before the difficult disturbance at the end. The warning consisted of three dots appearing in the road and moving "toward" the screen. They were visible for 15 seconds before they moved off the bottom of the screen. Three subjects completed 8 sessions each.



session*	1	2	3	4	5	6	7	8
disturbance	D	C	B	A	A	B	C	D
warning ?	yes				no			

*same order for all three subjects.

Figure 4. Experimental conditions.

Results: Long-term Performance Slope

Absolute error (from road centerline) was averaged every 32 seconds (E). Performance changes over the 40-minute run were taken as the average slope of E as a function of time, calculated with a least-squares linear regression. In 12 of the 24 runs, the slopes were significantly positive (indicating a performance decrement); in one case there was a significant, negative slope (improvement). (n=72, α =0.05, t > 2.0 for significance)

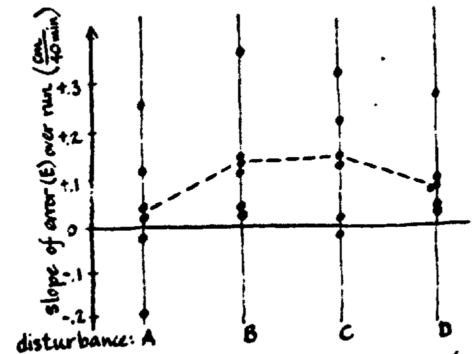


Figure 5. Performance decrement. (• - N.S.)

Taken together, there is no significant difference as a function disturbance but the trend seems to be in the direction opposite to what the facilitation hypothesis would suggest. There does, however, appear to be greater variability among the runs in the no-input case (A). Relative variability within runs was calculated as the ratio of the standard deviation of E (σ_E) to its mean ($\bar{E}$). With this measure, the no-input case (A) is worse, as might be suggested by the facilitation hypothesis. This is the same result observed in an earlier experiment using a CCTV driving simulator.[5]

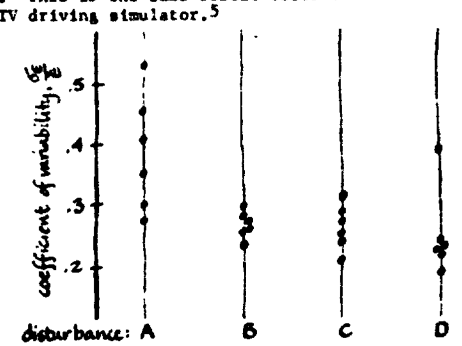


Figure 6. Relative variability within runs.

Results: Transition to Difficult Task

The last 32 seconds of each run was condition D. Performance as a function of the pre-condition (Figure 7) shows the same sort of results as for the average decrements (Figure 5): no significant difference between conditions and greater variability for the low-difficulty condition (A: no input). But the trend in this case is as the facilitation hypothesis would predict: better performance at intermediate difficulties.

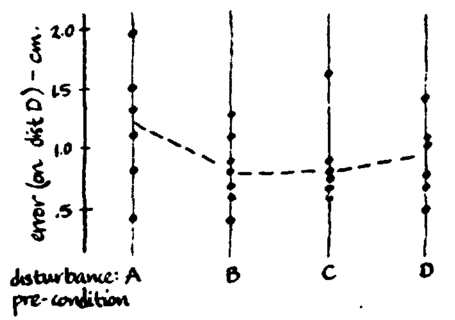


Figure 7. Performance (on D) at end of run.

INTERNAL UNCERTAINTY AS FACILITATION

Of particular interest is the case where there is no external disturbance. In some of these runs performance deteriorated, in some it did not and in at least one case it improved. Is there some way of predicting from a subject's instantaneous performance whether this is going to be a run where performance deteriorates or improves? One hypothesis is that the h.o. can "make the task interesting" or facilitating and thus sustain performance and avoid decrements.

Parameter Identification

The measure proposed in the next section requires identification of the h.o. transfer function. This was accomplished by identifying K_1, K_2 and τ in the following model from records of the h o. output.

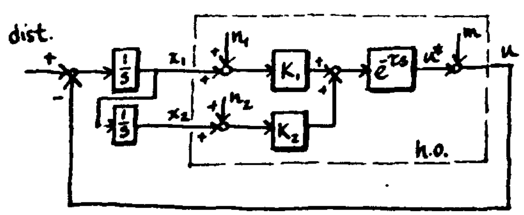


Figure 8. Parametric model used for identification.

Parameters K_1 and K_2 were estimated for different assumed τ by multiple regression $u(t) = K_1x_1(t-\tau) + K_2x_2(t-\tau)$, $t = nT$, $T = .03125$, $n = 1, 2, \ldots, 4096$. (i.e. 2 min at 32 Hz) Then the τ that gave the highest multiple correlation was chosen along with its K_1 and K_2. This method worked well, always giving a clear maximum correlation for τ in the expected range (.25 to .50 sec). The method of assuming a time-delay gives unbiased estimates, even without an external input disturbance, if the autocorrelation of the remnant is zero beyond τ.[6]

A Model for Internal Uncertainty

The measure proposed here as an indicator of facilitation is the information transmission rate. With no external disturbance input, the only information being transmitted is generated by the h.o. Two noise sources are hypothesized:

1. "input uncertainty" (n_1, n_2)
   band-limited white noises added to each observation and with variance proportional to the power of the variable being observed ($\sigma_{n_i}^2 = k_n \sigma_{x_i}^2$), and

2. "output uncertainty" (m)
   a white noise (limited to the same band) added to the h.o. output with $\sigma_m^2 = k_m \sigma_u^2$.

The information model used is for independent additive Gaussian signal (power density S(f)) and noise (power density N(f)).

$$I = \int_0^\infty \log_2\left(1 + \frac{S(f)}{N(f)}\right) df \qquad (1)$$

In my case, I assumed that what is being transmitted is the operator's uncertainty in his own output (m), the corrupting noise is due to n_1 and n_2, and the output of the channel is the "intended output" u^*. That is, the signal-to-noise ratio is computed at u^*.

Noise ratio calibration. Without direct access to these hypothesized noise processes, constant noise ratios (k_n, k_m) were assumed. For input uncertainty k_n = 0.01 was used based on results from the literature on manual control[7] and with corroboration from psychophysics[8].

No direct measurements have been made of motor noise ratios, so a simple calibration experiment was performed. The subjects were told to (without looking) make repeated, equal-amplitude, back-and-forth motions of the control-stick in time with a metronome. The same three subjects used four rates (1,2,3,4 moves/sec) and four approximate target distances (.5, 1, 2, 3 cm). The mean and standard deviation of movement distance were calculated for sequences of 20 moves where the extremes of motion were taken as the beginning and end of successive moves.

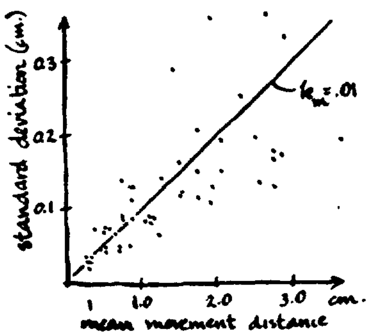


Figure 9. Output uncertainty from "blind-tapping" task.

The results show a constant ratio of the standard deviation to the mean (0.1) which is the same for all subjects and independent of frequency. Thus for output uncertainty, k_m = 0.01 which is the same ratio as for input uncertainty.

(In the information calculation k_n and k_m appear only as the ratio k_n/k_m, which is here assumed constant; a different value would shift all the results in the same direction: relatively more output uncertainty makes for more information transmitted.)

The "signal" and "noise" spectra at u^* are determined by the closed-loop transfer functions u^*/m, u^*/n_1 and u^*/n_2, which are calculated from parameters K_1, K_2 and τ taken from the h.o. identification.

$$\frac{S(f)}{N(f)} = \frac{\left|\frac{u^*}{m}\right|^2 k_m \sigma_m^2}{\left|\frac{u^*}{n_1}\right|^2 k_n \sigma_{n_1}^2 + \left|\frac{u^*}{n_2}\right|^2 k_n \sigma_{n_2}^2} \qquad (2)$$

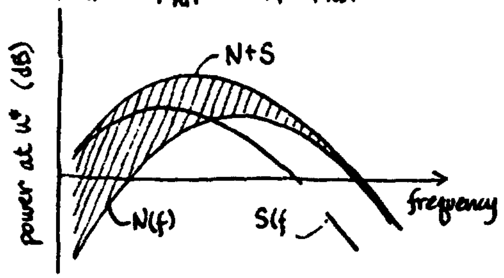


Figure 10. Components of power at u*.

The shaded area in Figure 10 represents the integral of log (S+N) - log (N), and thus the information transmitted, (equation (1)).

Substituting the parametric model for the transfer functions gives a formula for the signal-to-noise ratio as a function of frequency. The identified parameters K_1 and K_2 only appear as a ratio $T_L = K_1/K_2$ corresponding to the "lead time-constant" and the time-delay, τ, does not appear.

(3)

T_L, $\sigma_{n_1}^2$, $\sigma_{n_2}^2$ and σ_m^2 were measured for each two-minute segment of each run and then used in the model (1) and (3) to calculate the information transmitted (I). The averages of I for the six runs with no input disturbance show a positive correlation with the decrement in performance over the run (Figure 11).

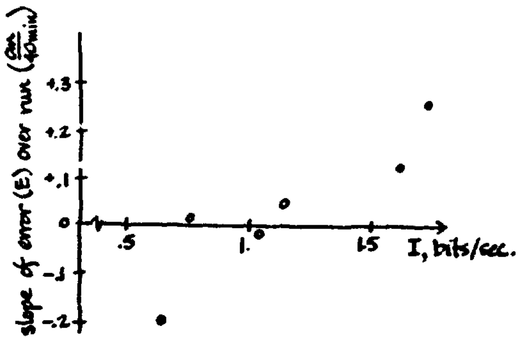


Figure 11. Performance decrement vs. "internal" information transmitted with no-input disturbance (A).

This is opposite to what the facilitation hypothesis would predict for low-stress tasks. It was thought that more information transmission or "self-induced work-load" would produce less performance decrement.

CONJECTURES

There are several possibilities: the proposed measure may not be a good indicator of facilitation, performance decrements might not be sensitive to facilitation, the facilitation hypothesis might be wrong in this case.

We do know that using just the external disturbance as a measure of difficulty (A,B,C,D) it is more difficult to predict what is going to happen over the run for the easier tasks and that some of that variability is correlated with the amount of "self-induced work-load".

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PERFORMANCE AND WORKLOAD ANALYSIS OF IN-FLIGHT HELICOPTER TASKS[a]

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SUMMARY

The study described in this paper was aimed at assessing the potentials of the optimal control model structure to predict the important characteristics of realistic operational helicopter missions.

The theoretical and experimental results indicate that the optimal control model succesfully predicts the best attainable (rather than the average) performance of a group of well-trained, highly motivated subjects. Furthermore, the model allows a description of inter-subject variability.

The control effort model predictions have been supported by subjective ratings. The model seems to provide a meaningful representation of pilot workload involved in complex control tasks.

INTRODUCTION

Many questions related to operating aircraft are still largely unresolved. The available handling quality criteria predominantly reflect the effect of the pilot on the vehicle. By the same token, operational research studies often exclusively concentrate on system performance. In spite of an increasing awareness of the necessity to emphasize the human operator's participation in manned vehicle systems, there are still very few satisfactory tools to describe his role in these systems. A promising approach concerns the use of mathematical models of human behavior. Among several different approaches toward human operator modeling, the optimal control model has emerged as the most useful one for the study of complex manned aerospace systems.

This model has been tested, so far, only against data obtained for (a variety of) laboratory tasks. The objective of the present study was to investigate the usefulness of the optimal control model structure (Refs.1-3) and a control effort model (Ref. 7) to describe realistic, in-flight aircraft control tasks. Especially, the use of the model as a predictive tool was concentrated on. For this, three helicopter instrument control tasks were investigated: a hover and two navigation tasks at prescribed heights.

In the following chapter some aspects of the optimal control and workload model are discussed. Next, the experimental program is described and the experimental results are compared with model predictions.

OPTIMAL CONTROL MODEL

The helicopter control tasks concerned are described in terms of the optimal control model (OCM). The inputs of the model which is documented extensively in the literature (e.g. Refs. 1 and 2) can be divided in task-related characteristics (parameters) and human operator parameters. The former comprise the system (helicopter) dynamics, the disturbance environment (moderate atmospheric translational gust is included) and the information available to the pilot to perform the task (via an integrated display). The latter can be considered as the real input parameters of the model or assumptions to be made:

- the objectives of the task (instructions) yielding a given control strategy. This is represented by the weighting matrices of the quadratic cost functional which is (assumed to be) minimized by the pilot's optimal control strategy
- an equivalent perceptual time delay which has been found to be relatively constant (0.20 sec)
- the attention dedicated to (observation noise corresponding with) the various displayed variables
- human randomness in executing control inputs which will be represented by a (constant) motor noise ratio of -25 dB (disturbances enter the system in parallel with the controls).

The cost functional weightings are selected on the basis of maximum allowable deviations, or limits. The choice of these for the present study will be discussed in the next chapter. The weightings for each quadratic term in the cost functional is then the inverse of the square of the corresponding limit.

The observation noise covariances have been found to be proportional to the mean-squared value of the displayed variables and inversely proportional to the square of the random input describing function gain associated with a threshold device. This threshold is in the following identified with the "acceptable" deviations of displayed variables ("indifference" thresholds). Furthermore, the interference model of reference 3 indicates that the covariances are inversely proportional to the fraction of attention f_i, paid to the displayed variable y_i. In formula

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a) This investigation has been carried out under contract for the Research Branch of the Directorate of Material Air RNLAF.

$$V_{y_i}(t) = \frac{\pi P_{0_i} E\left\{y_i^2(t)\right\}}{f_i K_{y_i}^2 (\sigma_{y_i}(t), a_{y_i}(t))} \qquad (1)$$

where P_{0_i} is the "noise/signal" ratio corresponding with "full attention" and has units of normalized power (positive frequencies) per rad/sec and K_{y_i} is the afore-mentioned gain.

For the display situation of the experimental program it is assumed that P_{0_i} is equal for all displayed variables: P_0. This indicates the overall level of attention paid to the task and is, just like the "indifference" threshold, a variable in the subsequent analysis. The allocation of attention among the displayed variables can be optimized (minimal cost functional). The formulation of this problem and its experimental support is contained in the next section.

Once the cost functional weightings, the "indifference" threshold and the overall level of attention are assumed (model inputs), a variety of measures of performance (variances are considered in the following) can be obtained as well as the corresponding workload. The latter is provided by the control effort model discussed in the following.

Optimal allocation of attention

In accordance with the fundamental assumption of optimality it can be assumed that the human operator divides his attention among the displayed variables optimally, i.e., minimizing the cost functional J (Ref. 4). So the problem is to minimize $J(f_y)$, subject to the (scalar) equality constraint

$$\sum_{i=1}^{M} f_{y_i} = 1 \qquad (2)$$

where M is the number of display indicators, and the (vector) inequality constraint

$$f_{y_i} \geqslant 0 \text{ for } i = 1,\ldots M$$

This is a standard parameter optimization problem which can be solved numerically by a first-order gradient method.

There is ample experimental evidence that the human operator derives from a given display indicator both displacement- and rate information*.

* It has been found that sometimes the human operator obtains also acceleration information from a display indicator (Ref. 6)

Relatively good model results have been obtained assuming equal attention (i.e. equal observation noise ratio) for displacement and rate. However, an alternative hypothesis is that the human operator divides his attention between displacement- and rate information. It is (again) assumed that this allocation of attention will be optimal (minimal cost functional) with the constraint $f_y + f_{\dot{y}} = 1$; in other words, the human operator divides his capacity optimally between all the display variables $(y_1, \dot{y}_1, \ldots y_M, \dot{y}_M)$.

Excellent experimental support for the foregoing hypothesis is provided by the model results of the experimental program of reference 7. In this study a variety of single-indicator tracking tasks (controlled element dynamics) was investigated. Accurate model results were obtained without the constraint of equal observation noise ratio for error displacement and error rate. Position, velocity and acceleration control tasks (K, K/s and K/s^2 dynamics, respectively) were considered with various instability levels. The results of four typical configurations are shown in figure 1. The "measured"* allocation of attention between error displacement and error rate is clearly quite close to the optimum (minimal cost functional). Although for the K/s^2 tasks no reliable (unique) observation noise ratios could be obtained**, also for these configurations the experimental results suggest an allocation of attention near the theoretical optimum (a fraction of attention to error rate of about 0.9).

Based on the foregoing results it will be assumed in the following analysis that the human operator (model) divides his information processing capacity optimally among the display variables (displacement and rate of all display indicators).

Control effort model

For a complete description of human control behavior and its impact on overall system reliability, it is necessary to assess how hard the human controller has to work to achieve a given performance (criterion). Because of the adaptive capabilities of the human operator control effort is often the most sensitive to control task characteristics under consideration. In this context a control effort model is developed in terms of the optimal control model parameters. This model is presented in reference 7.

* By matching performance scores of interest, as well as describing function and remnant data, model parameters (observation noise ratios) could be estimated quite accurately resulting in the "measured" fractions of attention.

** The performance measures are very insensitive to position noise ratio; furthermore, because of the important effect of motor noise, no unique rate observation noise ratio could be obtained.

Since a somewhat modified version of the model is used in the subsequent analysis (directed at multivariable control situations), the model is briefly reviewed in the following.

Human control response is partly determined by mechanisms that selectively tune the organism to the stimulus situation, by which is meant both selectively attending to some stimulus in preference to others and investing more or less attention per source of information. This can be identified with voluntary attention (Ref. 8), reflecting that the subject attends to the stimulus because of its relevance for performing the task and not only because of its arousal function. Also involuntary attention is included in the control effort model. This can be related to the level of arousal and is largely dictated by the properties of the displayed information.

The aspect of voluntary attention is incorporated in the model in terms of the overall level of attention, P_0. The aspect of involuntary attention is included in the control effort model in terms of the sensitivity of task performance (cost functional, J) to the momentary attention paid by the subject. In formula

$$E = S/P_0 \text{ (dB)} \tag{3}$$

with

$$S = \frac{\partial J}{\partial P_0} \text{ (dB)}$$

where the partial derivative indicates that the other model parameters are kept constant.

For the eight single-axis control tasks of the experimental program presented in reference 7 the computed control effort results are compared with subjective ratings. The result which is shown in figure 2 exhibits an excellent correlation between both.

EXPERIMENTAL PROGRAM

Experimental conditions

Several considerations were involved in the experimental set-up. In order to define (i.e., measure and model) accurately the (in-flight) helicopter tasks, instrument tasks were chosen allowing a complete description of the displayed information. An other consideration was to include various configurations respresenting a sufficient variation in workload to obtain significant experimental results.

Based on this, an instrument hover task was chosen consisting of stabilizing an Alouette III helicopter at a height of 100 ft with minimal horizontal (ground) speed. The three attitude angles were provided by a three-axis ADI presented in figure 3. Horizontal velocity components were presented via the cross pointers shown in the figure. A backward velocity of 5 kts corresponded with a full needle deflection upwards (all the display signs were chosen according to the "fly-to" principle). A height error of 100 ft corresponded with a display deviation of 2 dots.

Furthermore, two navigation tasks were chosen consisting of flying along a desired track with an indicated airspeed of 60 kts at a prescribed height: 600 and 150 ft, respectively. A track deviation of 200 ft corresponded with a full deflection of the vertical pointer shown in figure 3. A height error deflection of 2 dots corresponded with a height error of 100 ft for the navigation task at 600 ft and of 60 ft for the task at 150 ft. The subjects were instructed to maintain a constant indicated airspeed of 60 kts provided by the display shown in figure 3. So, apart from this indicator, all the information to perform the task was provided by the ADI.

Each sortie consisted of two hover tasks (of 3 min) and the two navigation tasks (of 5 min). Each subject performed two training flights to partially eliminate learning effects. For several reasons the program (9 sorties per subject) could not be completed; this is indicated by the number of replications given in the following tables.

All helicopter parameters of interest were recorded digitally; furthermore, subjective ratings were collected on the rating scales given in table 1. The four participating helicopter pilots had (on the average) a flying experience of 1200 hours of which 60 hours instrument flying. Figure 4 shows the Alouette III helicopter with the evaluation pilot (seated to the right), the safety pilot and the observer.

Experimental and model results

Since space does not permit an extensive presentation of the experimental results (these are given in reference 9), only the principal experimental results will be discussed corresponding with the model results. This implies that the results of two subjects of whom sufficient experimental data were obtained will be emphasized in the following.

Model predictions

Optimal control model predictions were obtained on the basis of the following assumptions:

- the cost functional weightings selected via the maximum allowable limits were chosen on the basis of the available understanding of the task requirements and physical- and display limits. The result is shown in table 2
- the indifference thresholds were zero and the overall level of attention was obtained by determining the "optimum" trade-off between system performance and attention ("knee" of the curve) supported by the results of an experimental program (Ref. 10) using the same display.

The predicted system performance scores and the optimum allocation of attention (an equal division of attention between longitudinal and lateral control has been assumed) are presented in table 3 for the HOVER task and in table 4 for the NAV-H task. Also the corresponding measurements are given. In the tables an overall performance index, J_m, is shown. This performance index incorporates the scores which were instructed to be minimized: height error (h) and horizontal speed (v_h) for the HOVER task and height error and lateral deviation (y) for the NAV tasks. These scores are weighed by the corresponding display limits, so that J_m is the sum of the meansquared fractions of the full display deviations. This criterion is analogous to the cost functional of the optimal control model were it is assumed that this criterion is minimized by the human operator.

The results in table 3 indicate that there is a substantial difference in hover performance between the three subjects. The model predictions concerning the guidance variables (height error, h, and total horizontal speed, v_h) are clearly too optimistic. However, the trend in performance between the subjects leads to the conclusion that the model predictions reflect the "limit" (optimum) of human control behavior (of the well-trained, well-motivated pilot). This is also applicable to the results of the NAV-H task. For this task the inter-subject variability is considerably less than for the HOVER task; therefore, also the average performance is given in table 4.

The experimental results of the NAV-L task are only significantly different from the NAV-H results with respect to the height performance. The model did (exactly) predict this performance improvement for the NAV-L task (RMS h_L/RMS h_H = 0.8).

The assumption that no thresholds are involved in observing the display quantities is reasonable to the extent it is related to the quality of the displays involved in the experiment. This was the consideration for neglecting the thresholds. However, the assumption is not in accordance with pilot's control behavior in real flight: within certain limits the pilots tolerate display deviations (do not take any control actions) (Refs. 11 and 12). Thus, a second "prediction" was made assuming an indifference threshold (TH) of 1/6 of the full display deflections of the guidance variables (h,u, v,y). Only the performance scores of the pertinent guidance variables were affected by this assumption (as might be expected). The resulting scores are given (between parentheses) in tables 3 and 4.

In summary, it can be concluded from the foregoing that the optimal control model predictions do reflect optimal control behavior, i.e., the model results represent the best attainable performance. To put another way, the model predictions may not be considered as describing the <u>average</u> pilot's control behavior but the <u>best</u> pilot's performance.

The following paragraph deals with the question which model assumptions have to be modified in order to obtain a better agreement between model and experimental results.

Model match

Based on the experimental and model results the following parameters were changed in order to match the experimental results of subjects A and B.

- The maximum allowable limits corresponding with the cost functional weightings on attitude angles and control deflections were somewhat diminished. The pertinent values are given in table 2.
- For subject A an indifference threshold of 1/6 was assumed (a threshold of 1/6 of the full display deflections of the guidance variables) and for subject B (considerably less motivated) a ratio of 1/2 was taken.
- An optimal division of attention between longitudinal and lateral control was determined and the overall level of attention, P_0, was obtained by <u>matching</u> the overall performance index, J_m.

The resulting model scores are compared with the measured scores for both subjects for the HOVER task in table 5. Apart from the substantial difference in heading scores*, all the important performance scores match well**.

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* This difference is possibly due to an inaccuracy in the description of the vehicle dynamics (stability and control derivatives). At any rate, even a substantial variation of all model parameters could not remove this discrepancy.

** In order to match the height score of subject B it had to be assumed that somewhat less attention was paid to height and forward speed information than the optimal amount.

Table 6 presents the model and experimental results of subject A of the NAV tasks. As the difference in performance between the NAV-H and the NAV-L task seems insignificant, no attempt has been made to model the tasks separately. All scores match quite well, suggesting that the model provides a good description of pilot behavior for both tasks. In table 7 the results of subject B are given for both NAV tasks. The NAV-H results were obtained as indicated before. For the NAV-L match the maximum allowable limit of 60 ft full display deflection was used for the weighting on height error*. It had to be assumed that subject B spent somewhat more attention to longitudinal control than subject A (.08). Again, all the model scores match reasonably well the corresponding measurements.

In summary, it can be concluded from the foregoing that for all the configurations considered a good agreement between measured scores and model results could be obtained on the basis of reasonable assumptions and basically two model parameters: the indifference threshold ratio and the overall level of attention. The first parameter can be related to the motivation of the pilot which appears to vary substantially between the subjects participating in the present experiment. The latter parameter reflects also to some extent the motivation of the subject. Moreover, it is partly dictated by the task (demand of the task). This will be discussed in the next section.

Control effort model results and subjective ratings

In this chapter the foregoing model results are used to compute the corresponding control effort. These results are compared with subjective ratings. Because of the limited data base this analysis must be considered as exploratory.

For subject A control effort has been computed for the HOVER task and the NAV tasks. Also the theoretical curves of system performance versus control effort have been established. The result is shown in figure 5. The model predicts that the HOVER task is more demanding than the NAV-tasks. Furthermore the figure shows that the HOVER performance is more sensitive to attention (or effort) than the NAV performance. This explains why the inter-subject variability is much larger for the HOVER task than for the NAV tasks and visualizes the greater demand of the HOVER task (the HOVER task "forces", but also enables, the subjects to spent that much effort). For subject B control effort has been computed for all three tasks. Again the model predicts that the highest workload is involved in performing the HOVER task.

The control effort model results are compared with subjective ratings in table 8. Also the ratings indicate that the HOVER task is the most difficult. Furthermore, on the average, there is no significant difference in effort between the NAV-L and the NAV-H task. This is even more clearly illustrated comparing the average ratings of all subjects with the corresponding model predictions. This is also presented in table 8.

In summary, it can be concluded that the control effort model predictions have been supported by the subjective ratings. This provides additional validation for the model which, so far, has been tested only against data obtained for (a variety of) laboratory tasks.

CONCLUSIONS

The objective of the present program was to investigate the usefulness of the optimal control structure and the control effort model to predict and describe performance and effort of realistic helicopter control tasks. Referring to the results presented in the previous chapter the following specific conclusions can be drawn.

- The optimal control model can succesfully be used to predict the (best attainable) performance of in-flight (helicopter) control tasks.
- In real flight circumstances the pilot tolerates display deviations within certain limits. This can be taken into account in the optimal control model by assuming (statistical) thresholds in perceiving these variables.
- The rationale for selecting the weightings in the cost functional of the model - which can be related to the assumption concerning the pilot's control strategy - is convincingly supported by the experimental results.
- The model provides a suitable framework to formulate differences in control behavior between subjects, basically in terms of two model parameters: the indifference threshold ratio and the overall level of attention. Both reflect personality traits, such as motivation.
- The control effort model predictions have been supported by subjective ratings for the three helicopter tasks under investigation. Although additional experimental support for the model is desirable, it seems to provide a meaningful representation of pilot workload involved in complex control tasks.

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* This subject performed the HOVER task with various horizontal speed display sensitivities (5 and 25 kts full display deflections). He maintained a surprisingly constant level of horizontal speed performance in terms of display deviations and not in units of kts. This excellently supports the assumption involved in the optimal control modeling that the pilot's control strategy is such that the display deviations are within an "acceptable" region.

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Table 1: Rating scales

Name:

Task:

Using the scale below, indicate the degree of effort you spend on performing the task

0 1 2 3 4 5 6 7 8 9 10

increasing effort

Rating scale for Controllability and Precision

- 0
- Extremely easy to control with excellent precision
- 1
- 2
- Very easy to control with good precision
- 3
- 4
- Easy to control with fair precision
- 5
- 6
- Controllable with somewhat inadequate precision
- 7
- Controllable, but only very imprecisely
- Difficult to control
- 8
- Very difficult to control
- 9
- Nearly uncontrollable
- 10 ☐ Uncontrollable
- ☐ Not applicable

Rating Scale for Demands on Pilot

- 0
- 1
- 2
- Completely undemanding, very relaxed and comfortable
- 3
- Largely undemanding relaxed
- 4
- 5
- Mildly demanding of pilot attention, skill, or effort
- 6
- Demanding of pilot attention, skill, or effort
- 7
- Very demanding of pilot attention, skill, or effort
- 8
- Completely demanding of pilot attention, skill, or effort
- 9
- Nearly uncontrollable
- 10 ☐ Uncontrollable
- ☐ Not applicable

Parameter		HOVER allowable limit	NAV allowable limit
θ	(rad)	0.15 (0.1)	0.1
ϕ	(rad)	0.15 (0.1)	0.1
ψ	(rad)	0.15 (0.1)	0.1
u	(kts)	5	10 (15)
v	(kts)	5	-
h	(ft)	100	100
y	(ft)	-	100(H) - 60(L)
δ_e	(rad)	0.2 (0.1)	
δ_a	(rad)		
δ_r	(rad)		
CP	(rad)		
$\dot{\delta}_e$	(rad/sec)	0.4 (0.2)	
$\dot{\delta}_a$	(rad/sec)		
$\dot{\delta}_r$	(rad/sec)		
$\dot{CP}$	(rad/sec)		

between parentheses the values used for the matched model results; otherwise, the pre- and post-experimental values are identical.

Table 2: Allowable limits used for the cost functional weightings

PARAMETER		MODEL PRED.	MEASURED SUBJECT A	MEASURED SUBJECT B	MEASURED SUBJECT C
σ_θ	(deg)	1.6	1.7	1.6	1.4
σ_ϕ	(deg)	1.0	1.6	1.3	1.6
RMS ψ	(deg)	4.3	2.5	4.8	4 5
RMS h	(ft)	13.1(16.3)	21.3	55.1	100.4
RMS u	(kts)	0.8(1.0)	1.5	2.5	2.8
RMS v	(kts)	0.4(0.7)	1.2	1.6	2.2
RMS v_h	(kts)	0.9(1.2)	1.9	3.0	3.5
σ_{δ_e}	(deg)	1.1	1.1	1.0	0.7
σ_{CP}	(deg)	1.1	1.1	0.8	0.4
σ_{δ_a}	(deg)	0.2	0.6	0.5	0.6
σ_{δ_r}	(deg)	1.7	1.1	0.6	0.7
Overall performance J_m		0.05(0.09)	0.20	0.66	1.49
Replications		-	15	5	3

ALLOCATION OF ATTENTION	
θ	.00
$\dot{\theta}$	.11
ϕ	.00
$\dot{\phi}$	.01
ψ	.05
$\dot{\psi}$	.14
h	.05
$\dot{h}$	.04
u	.02
$\dot{u}$	.29
v	.02
$\dot{v}$	.28
f_{LONG}	.5
P_0	-18 dB

(.): predictions with thresholds

Table 3: Model predictions and experimental results for the HOVER task

PARAMETER		MODEL PRED.	MEASURED SUBJECT A	B	C	D	AVERAGE
σ_θ	(deg)	0.9	2.6	1.9	2.2	1.8	2.2
σ_φ	(deg)	2.8	2.8	2.4	3.1	2.4	2.7
σ_φ	(deg)	3.6	4.9	6.2	6.6	3.6	5.5
RMS h	(ft)	12.5(15.4)	25.4	41.3	39.3	35.6	35.9
RMS u	(kts)	0.8(1.4)	5.2	6.5	7.3	7.0	6.6
RMS y	(ft)	38.7(43.2)	43.0	84.5	66.3	76.8	69.4
RMS $\dot{y}$	(kts)	4.1	3.7	4.7	4.6	4.0	4.3
σ_{δ_e}	(deg)	0.7	0.8	0.7	0.6	0.5	0.7
σ_{CP}	(deg)	0.9	1.2	1.2	0.5	0.3	0.9
σ_{δ_a}	(deg)	1.5	0.4	0.4	0.4	0.3	0.4
σ_{δ_r}	(deg)	1.2	0.9	1.0	0.6	0.4	0.8
Overall performance, J_m		0.05(0.07)	0.11	0.35	0.26	0.27	0.25
Replications		.	9	7	5	3	24

ALLOCATION OF ATTENTION	
θ	.19
$\dot{\theta}$	.21
φ	.08
$\dot{\varphi}$	.16
ϕ	.07
$\dot{\phi}$	.11
h	.03
$\dot{h}$	.04
u	.03
y	.01
$\dot{y}$	.07
f_{LONG}	.5
P_0	-18 dB

(.): predictions with thresholds

Table 4: Model predictions and experimental results for the NAV-H task

PARAMETER		SUBJECT A MODEL	SUBJECT A MEASURED	SUBJECT B MODEL	SUBJECT B MEASURED
σ_θ	(deg)	2.1	1.7	2.1	1.6
σ_φ	(deg)	1.4	1.6	1.5	1.3
RMS ϕ	(deg)	6.8	2.5	7.8	4.8
RMS h	(ft)	22.3	21.3	54.5	55.1
RMS u	(kts)	1.5	1.5	2.1	2.5
RMS v	(kts)	1.2	1.2	1.7	1.6
RMS v_h	(kts)	1.9	1.9	2.7	3.0
σ_{δ_e}	(deg)	1.0	1.1	1.0	1.0
σ_{CP}	(deg)	0.8	1.1	0.8	0.8
σ_{δ_a}	(deg)	0.2	0.6	0.14	0.5
σ_{δ_r}	(deg)	1.6	1.1	1.7	0.6
Overall performance, J_m		0.20	0.20	0.[illegible]	0.66
f_{LONG}		0.57		0.57	
P_0		-16 dB		-15 dB	
Threshold ratio TH		1/6 display limit		1/2 display limit	

Table 5: Model "match" and experimental results of the HOVER task

PARAMETER		MODEL "MATCH"	MEASURED NAV-H	NAV-L
σ_θ	(deg)	1.9	2.6	2.1
σ_φ	(deg)	2.9	2.8	2.8
σ_ϕ	(deg)	3.6	4.9	4.7
RMS h	(ft)	24.0	25.4	23.9
RMS u	(kts)	2.5	5.2	5.1
RMS y	(ft)	44.6	43.0	46.6
RMS $\dot{y}$		4.1	3.7	3.9
σ_{δ_e}	(deg)	0.6	0.8	0.8
σ_{CP}	(deg)	0.6	1.2	1.1
σ_{δ_a}	(deg)	1.3	0.4	0.4
σ_{δ_r}	(deg)	1.0	0.9	0.8
Overall performance, J_m		0.11	0.11	0.11

ALLOCATION OF ATTENTION	
θ	.12
$\dot{\theta}$	.07
φ	.08
$\dot{\varphi}$	.30
ϕ	.07
$\dot{\phi}$	.14
h	.04
$\dot{h}$	.02
u	.00
y	.02
$\dot{y}$	.14
f_{LONG}	.25
P_0	-16.4 dB
TH	1/6

Table 6: Model "match" and experimental results of the NAV tasks for subject A

PARAMETER		NAV-H MODEL	NAV-H MEAS.	NAV-L MODEL	NAV-L MEAS.
σ_θ	(deg)	2.1	1.9	1.9	1.6
σ_φ	(deg)	3.1	2.4	3.3	2.8
σ_ϕ	(deg)	4.1	6.2	4.4	5.8
RMS h	(ft)	41.7	41.3	28.3	27.2
RMS u	(kts)	2.8	6.5	2.5	5.7
RMS y	(ft)	80.0	84.5	85.0	88.7
RMS $\dot{y}$	(kts)	4.7	4.7	5.0	5.1
σ_{δ_e}	(deg)	0.7	0.7	0.6	0.6
σ_{CP}	(deg)	0.6	1.2	0.8	1.0
σ_{δ_a}	(deg)	1.3	0.4	1.3	0.4
σ_{δ_r}	(deg)	1.0	1.0	1.0	0.8
Overall performance, J_m		0.33	0.35	0.26	0.27

ALLOCATION OF ATTENTION PAR.	NAV-H	NAV-L
θ	.12	.16
$\dot{\theta}$	.07	.09
φ	.08	.07
$\dot{\varphi}$	.30	.27
ϕ	.07	.06
$\dot{\phi}$	.14	.12
h	.04	.05
$\dot{h}$	.02	.03
u	.00	.00
y	.02	.02
$\dot{y}$	.14	.13
f_{LONG}	.25	.33
P_0	-15.4 dB	
TH	1/2	

Table 7: Model "match" and experimental results of the NAV tasks for subject B

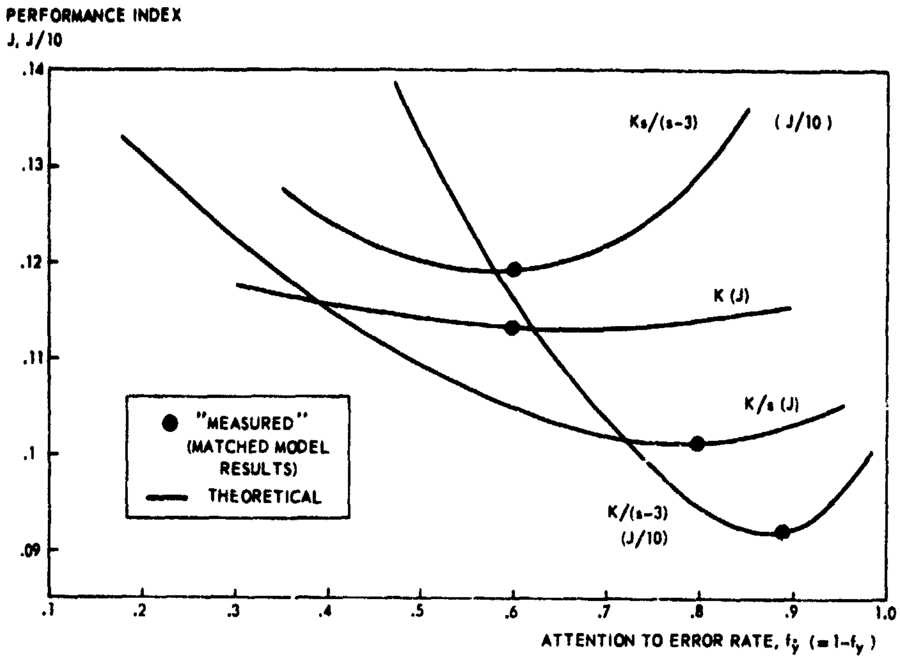


FIG. 1 ALLOCATION OF ATTENTION VERSUS PERFORMANCE-THEORETICAL AND MEASURED RESULTS. (DERIVED FROM REF. 7)

SUBJECT	TASK	COMPUTED EFFORT	SUBJECTIVE RATING		
			AVERAGE	EFFORT	DEMAND
A	HOVER	17.0	5.3	5.0	5.5
	NAV-L	15.9	4.9	4.5	5.4
	NAV-H	15.9	4.6	4.3	4.8
B	HOVER	16.5	7.5	7.5	7.4
	NAV-L	15.1	6.4	6.4	6.4
	NAV-H	14.9	6.7	6.7	6.7
Average of 4 subjects	NAV-L	15.0	5.3	5.2	5.5
	NAV-H	15.1	5.4	5.2	5.7

Table 8: Comparison of control effort model results and subjective ratings

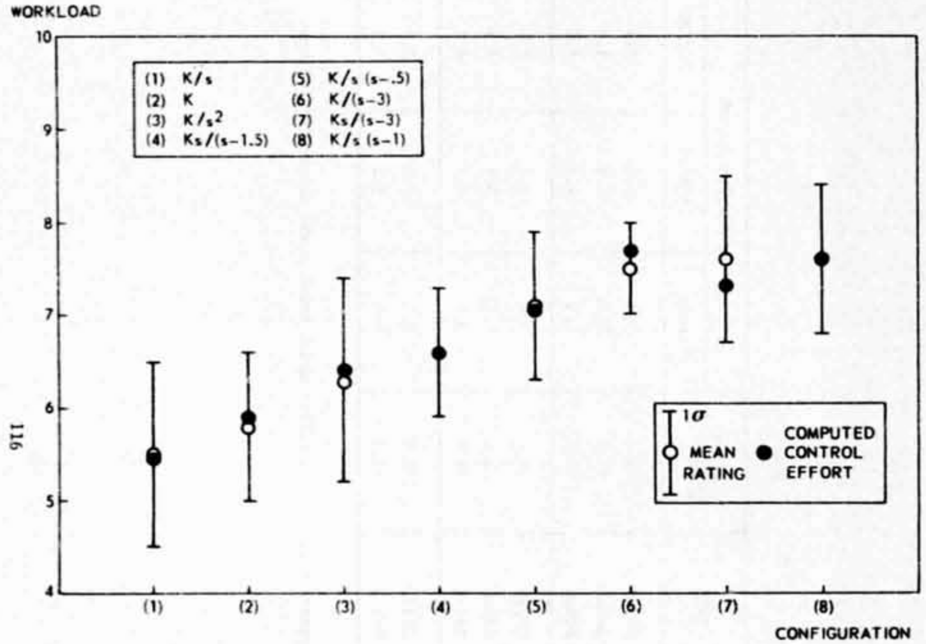
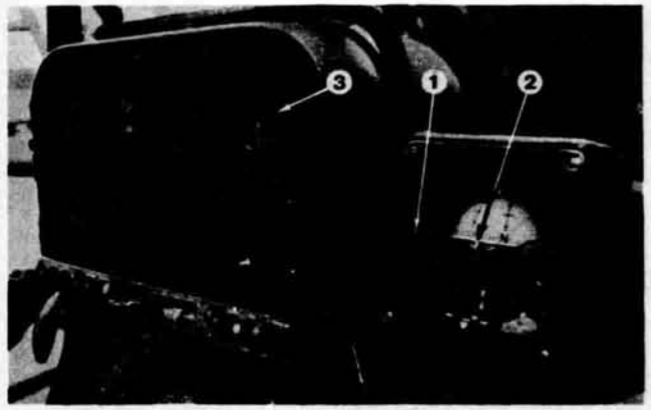


FIG. 2 A COMPARISON OF COMPUTED CONTROL EFFORT AND SUBJECTIVE RATINGS.(DERIVED FROM REF. 7)



(1) HEIGHT ERROR
(2) HORIZONTAL VELOCITIES (HOVER) / LATERAL TRACK DEVIATION (NAV)
(3) INDICATED AIRSPEED (NAV)

FIG. 3 ALOUETTE III FLIGHT INSTRUMENTS

FIG. 4 ALOUETTE III HELICOPTER

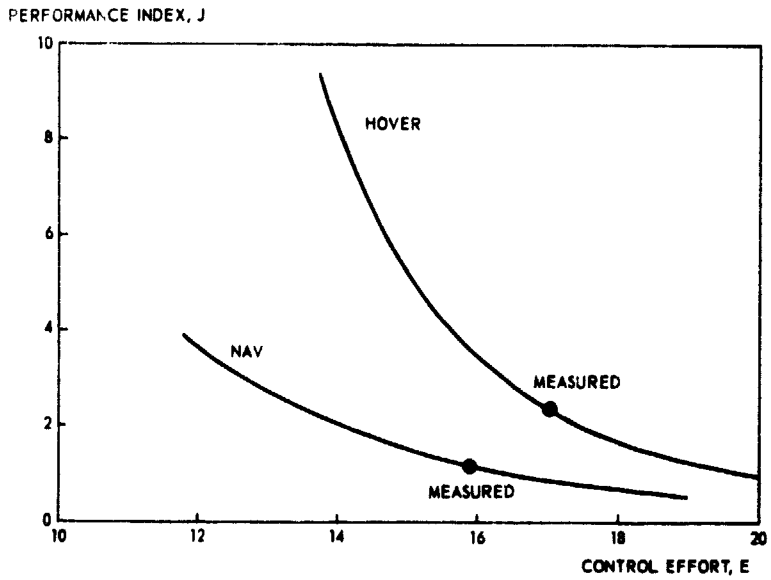


FIG. 5 PERFORMANCE VERSUS CONTROL EFFORT FOR SUBJECT A.